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ORIGINAL ARTICLE

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Intelligent aircraft maintenance support system using genetic algorithms and case-based reasoning

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Abstract The maintenance of aircraft components is crucial for avoiding aircraft accidents and aviation fatalities. To provide reliable and effective maintenance support, it is important for the airline companies to utilise previous repair experience with the aid of advanced decision support technology. Case-based reasoning (CBR) is a machine learning method that adapts previous similar cases to solve current problems. To effectively retrieve similar aircraft maintenance cases, this research proposes using a CBR system to aid electronic ballast fault diagnosis of Boeing 747-400 airplanes. By employing genetic algorithms (GA) to enhance dynamic weighting and the design of non-similarity functions, the proposed CBR system is able to achieve superior learning performance as compared to those with either equal/varied weights or linear similarity functions.

Keywords Aircraft maintenance · Electronic ballast · Case-based reasoning · Genetic algorithms

1 Introduction

Airplanes in operation throughout the world call for appropriate maintenance to assure flight safety and quality. When faults emerge in an aircraft component, actions for fault diagnosis and troubleshooting must be executed promptly and effectively. An airplane consists of many electronic components among which the electronic ballast is one common component to control fluorescent lamps in the cabin. The electronic ballast plays an important role in providing proper lights for passengers and flight crews during a flight. Unstable cabin lighting, such as flash and ON/OFF problems, is a common problem occurring in airplanes. An airplane usually has hundreds of electronic ballasts mounted in panels, such as light deflectors in fluorescent lamp fixtures. When an electronic ballast is abnormal, it has to be removed and sent to the accessory shop for further investigation.

The maintenance records for electronic ballasts generally contain information about the number of defective units found, the procedures taken, and the inspection or repair status. Basically these records are stored and used to assist mechanics in identifying faults and determining the components where repair or replacement is necessary. This is because previous similar solutions may provide valuable troubleshooting clues for new faults.

Similar to the analogy, CBR is a machine learning method that adapts previous similar cases to solve current problems. CBR shows significant promise for improving the effectiveness of complex and unstructured decision making. It is a problem-solving technique that is similar to the decision making process used in many real-world applications. This study considers CBR an appropriate approach to aid aircraft mechanics in dealing with the electronic ballast maintenance problem. Basically CBR systems make inferences using analogy to obtain similar experiences for solving problems. Similarity measurements between pairs of features play a central role in CBR [1]. However the design of an appropriate case-matching process in the retrieval step is still challenging. For the effective retrieval of previous similar cases, this research develops a CBR system with GA mechanisms used to enhance dynamic feature weighting and the design of non-similarity functions. GA is an optimisation technique inspired by biological evolution [2]. Based upon the natural evolution concept, GA works by breeding a population of new answers from the old ones using a methodology based on

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survival of the fittest. In this research, GA is used to determine not only the fittest non-linear similarity functions, but also the optimal feature weights.

By using GA mechanisms to enhance the case retrieval process, a CBR system is developed to aid electronic ballast fault diagnosis of Boeing 747-400 airplanes. Three hundred electric ballast maintenance records from Boeing 747-400 airplanes were gathered from the accessory shop of one major airline in Taiwan. The results demonstrated that an approach with non-linear similarity functions and dynamic weights indicates better learning performance than other approaches with either linear similarity functions or equal/varied weights.

2 Literature review

2.1 Case-based reasoning

CBR is a relatively new method in artificial intelligence (AI). It is a general problem-solving method that takes advantage of the knowledge gained from experience and attempts to adapt previous similar solutions to solve a particular current problem. As shown in Fig. 1, CBR can be conceptually described by a CBR-cycle that composes of several activities [3]. These activities include (1) retrieving similar cases from the case base, (2) matching the input and retrieved cases, (3) adapting solutions suggested by retrieved similar cases to better fit the new problem; and (4) retaining the new solution once it has been confirmed or validated.

A CBR system gains an understanding of the problem by collecting and analysing case feature values. In a CBR system, the retrieval of similar cases relies on a similarity metric which is used to compute the distance between pairs of case features. Generally, the performance of the similarity metric and the feature weights are keys to the CBR [4]. A CBR system could be ineffective in retrieving similar cases if the case-matching mechanism is not appropriately designed.

For an aircraft maintenance problem, CBR is a potential approach in retrieving similar cases for diagnosing faults as well as providing appropriate repair solutions. Several researches applied CBR to solve various airlines industry problems. Richard [5] developed CBR diagnostic software for aircraft maintenance. Magaldi [6] proposed applying CBR to aircraft troubleshooting on the flight line. Other CBR applications included flight condition monitoring and fault diagnosis for aircraft engine [7], service parts diagnosis for improving service productivity [8], and data mining for predicting aircraft component replacement [9].

Most of these CBR systems applied n-dimension vector space to measure the similarity distance between input and retrieved cases. For example, Sylvain et al. [9] adopted the nearest neighbourhood method. However, seldom have researchers attempted to employ dynamic weighting with non-linear similarity functions to develop fault diagnosis models for aircraft maintenances.

2.2 Genetic algorithms for feature weighting

In general, feature weights can be used to denote the relevance of case features to a particular problem. Wettschereck et al. [10] made an empirical evaluation of feature-weighting methods and concluded that feature-weighting methods have a substantially higher learning rate than un-weighted k-nearest neighbour methods. Kohavi et al. [11] observed that feature weighting methods have superior performance as compared to feature selection methods. When some features are irrelevant to the prediction task, Langley and Iba [12] pointed out that appropriate feature weights can substantially increase the learning rate.

Several researches applied GA to determine the most suitable feature weights. GA is a technique of modelling the genetic evolution and natural selection processes. A GA procedure usually consists of chromosomes in a population, a 'fitness' evaluation function, and three basic genetic operators called reproduction, crossover and mutations. Initially, chromosomes in the form of binary strings are generated randomly as candidate solutions to the addressed problem. A fitness value associated with each chromosome is subsequently computed through the fitness function representing the value of the candidate solution. Chromosomes with higher fitness values are selected to generate better offspring for the new population through genetic operators. Conceptually, the unfit are eliminated and the fit survive to contribute genetic material to the subsequent generations.

Wilson and Martinez [13] proposed a GA-based weighting approach which had better performance than the un-weighted k-nearest neighbour method. For large-scale feature selection, Siedlecki and Sklansky [14] introduced a 0–1 weighting process based on GAs. Kelly and Davis [15] proposed a GA-based on the weighted K-NN approach (GA-WK-NN) which had a lower error rates than the standard K-NN one. Brill et al. [16]

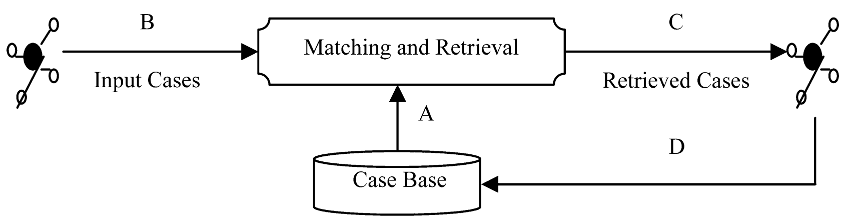


Fig. 1 A CBR cycle

demonstrated fast feature selection using GAs for neural network classifiers.

Though the above research used GA mechanisms to determine the feature weights for case retrieval, seldom did a study apply the GA to simultaneously determine features weights and corresponding similarity functions in a non-linear way. This paper attempts to apply GA mechanisms to determine both the optimal feature weights and the most appropriate non-linear similarity functions for case features. A CBR system is developed to diagnose the faulty accessories of electronic ballasts for Boeing 747-400 airplanes.

3 Methodology

3.1 Linear similarity

From the case base, a CBR system retrieves an old case that is similar to the input case. As shown in Fig. 2, the retrieval process is based on comparing the similarities for all feature values between the retrieved case and the input case, where f^{i}_{I} and f_i^R are the values of feature i in the input and retrieved case, respectively. There are many evaluation functions for measuring the degree of similarity. One numerical function using the standard Euclidean distance metric is shown in Eq. 1, where W_i is the ith feature weight. The feature weights are usually statically assigned to a set of prior known fixed values or all set equal to 1 if no arbitrary priorities determined.

$$\sqrt{\sum_{i=1}^{n} W_i \times (f_i^I - f_i^R)^2} \quad (1)$$

	Features						
Retrieved Case	f_1^R	f_2^R	f_3^R	...	f_i^R	...	f_n^R
Input Case	f_1^I	f_2^I	f_3^I	...	f_i^I	...	f_n^I

Fig. 2 Feature values

3.2 Non-linear similarity

Based on Eq. 1, this study proposed a non-linear similarity approach. The difference between the linear similarity and non-linear similarity is the distance function definition. For a non-linear similarity approach $(f_i^I - f_i^R)^2$ is replaced by the distance measurement $[(f_i^I - f_i^R)^2]^k$ as shown in Eq. 2.

$$\sqrt{\sum_{i=1}^{n} W_i \times \left[(f_i^I - f_i^R)^2\right]^k} \quad (2)$$

Where k is the exponent of the standard Euclidean distance function for the corresponding input and retrieved feature values. A GA mechanism is proposed to compute the optimal k value for each case feature. The range of exponent k is scaled from 1/2, 1/3, 1/4, 1/5, 1, 2, 3, 4 and 5. Figure 3 depicts an example equation $y = x^k$; where $x \in [0, 1]$ with various combinations of k.

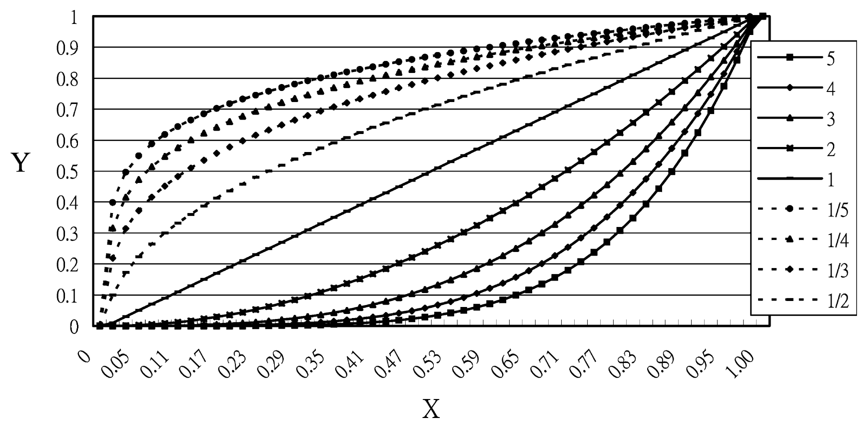
3.3 Static feature weighting

In addition to the linear or non-linear type of similarity function, feature weights W_i can also influence the distance metric. Feature weighting can be either static or dynamic. The static weighting approach assigns fixed feature weights for all case features throughout the entire retrieval process. For static feature weighting, each feature's weight can either be identical or varied. The feature weights are usually statically assigned to a set of prior known fixed values or equal to 1 if no arbitrary priorities are determined. For varied feature weighting, this study proposed another GA mechanism to determine the most appropriate weight for each feature.

3.4 Dynamic feature weighting

For the dynamic weighting approach, feature weights are determined according to the context of each input

Fig. 3 Illustration for linear and non-linear functions



case. As shown in Fig. 4, for a given input case, there are m retrieved cases in the case base, where $i = 1$ to n, n is the total number of features in a case, $j = 1$ to m, m is the total number of retrieved cases in a case base. f_{ij}^{R} is the ith feature value of the retrieved case$_j$, and f_i^{I} is the of the ith feature value of the input case. O_j^{R} is the outcome feature value of the jth retrieved case and O^{I} is the outcome feature value of the input case.

Assume that the outcome feature value is categorical data with p categories. For those features of categorical values, the weights are computed using Eq. 3.

$$W_i = Max\left(\frac{L_{it}}{E_i}\right) \tag{3}$$

where $i = 1$ to n, n is the number of case features in a case; $t = 1$ to p, p is the number of categories for the outcome feature. E_i is the number of retrieved cases of which f_{ij}^{R} is equal to f_i^{I}. L_{it} is the number of retrieved cases of which f_{ij}^{R} is equal to f_i^{I} and O_j^{R} is the tth categories.

For continuous values, their weights are not generated in the same way as described above unless the feature values are discretised in advance. Though there may exist various methods of discretisation, this study proposed another GA mechanism to discretise the continuous feature values. For the ith feature, a GA procedure is used to compute the optimal value, say A_i, to form a range centered on f_i^{I}. Let K_i denote the number of cases whose f_{ij}^{R} is between $(f_i^{I} - A_i)$ and $(f_i^{I} + A_i)$. Thus, E_i is replaced by K_i in Eq. 3. Feature weights are computed as shown in Eq. 4.

$$W_i = Max\left(\frac{L_{it}}{K_i}\right) \tag{4}$$

Based on Eq. 3 and Eq. 4, each input case has a corresponding set of feature weights in this dynamic weighting approach.

3.5 Experiment design

Since both the feature weights and similarity measurements between pairs of features play a vital role in case retrieval, this research investigated the CBR performance by observing the effects resulting from the combinations of different feature weighting approaches and similarity functions.

As indicated in Fig. 5, there are six approaches that combine different types of similarity functions and feature weighting methods. These are the linear similarity function with equal weights (approach A), linear similarity function with varied weights (approach B), non-linear similarity function with equal weights (approach C), non-linear similarity function with varied weights (approach D), linear similarity function with dynamic weights (approach E) and non-linear similarity function with dynamic weights (approach F).

The differences between the three feature weighting approaches are described as follows. For the equal weights approach, feature weights are all set equal to 1. For the varied weights approach, there is only one set of feature weights determined by a proposed GA

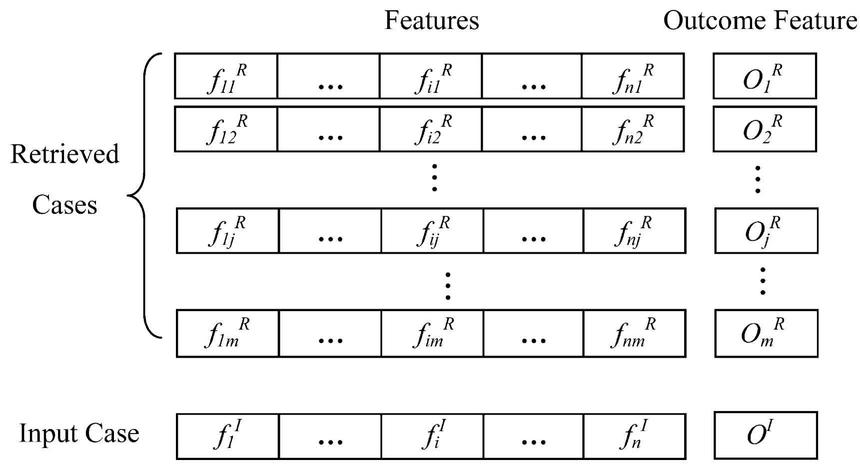


Fig. 4 Denotation of features and outcome feature values

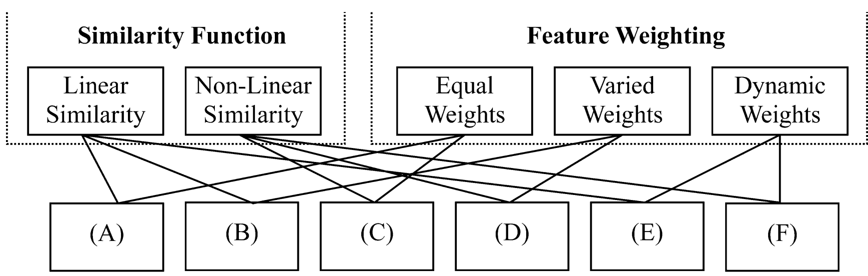


Fig. 5 Combinations of similarity functions and feature weighting methods

procedure. For the dynamic weights approach, there is a corresponding set of feature weights for each input case. That is, sets of feature weights are dynamically determined according to the input case.

4 Experiment and results

4.1 Case description

The aircraft electronic ballasts used to drive fluorescent lamps can be mounted on a panel such as the light deflector of a fluorescent lamp fixture. The fluorescent lamps initially require a high voltage to strike the lamp arc and maintain a constant current. Usually there is a connector at one end of the unit for the routing of all switching and power connections. As shown in Fig. 5, the electronic ballast operates from control lines of 115-vac/400 Hz aircraft power. When the operation power is supplied, the electronic ballast will start and operate two rapid start fluorescent lamps or single lamp in the passenger cabin of various commercial aircrafts, such as Boeing 747-400, 737-300, 737-400, 747-500 etc. There are two control lines connecting the ballast set and control panel for ON/OFF and BRIGHT/DIM modes among which DIM mode is used at night when the cabin personnel attempt to decrease the level of ambient light in the cabin.

Three hundred electric ballast maintenance records from the Boeing 747-400 were taken from the accessory shop of one major airline in Taiwan to construct the trouble-shooting system. Each maintenance case contains seven features identified as highly related to abnormal electric ballast operations. In Table 1, these features are either continuous or categorical. The outcome feature is the categories of the replaced parts set. For instance, category C_1 denotes the replaced parts of a transformer (illustrated as T101 on a printed circuit board) and a capacitor (illustrated as C307 on a printed circuit board). Category C_2 denotes the replaced parts of an integrated circuit (illustrated as U300 on a printed circuit board), a transistor (illustrated as Q301 on a printed circuit board) and a fuse (illustrated as F401 on a printed circuit board). Each category in the outcome feature represents a different set of replaced parts.

4.2 GA implementation

According to the experiment design, this study implements three GA procedures to determine (1) the optimal exponent k in the non-linear similarity functions, (2) the most appropriate set of varied weights for static feature weighting and (3) sets of feature weights for dynamic feature weighting. Several steps are required in developing a GA computer program. These steps include chromosome encoding, fitness function specification, and internal control parameter specification. The details of each step according to the order of three GA applications are described as follows.

4.2.1 Non-linear similarity

Chromosomes are designed for encoding the exponent k in the non-linear similarity functions. Because there are six features in a case, a chromosome was composed of six genes to encode the exponents in the six corresponding non-linear functions. Each chromosome is assigned a fitness value based on Eq. 5. The population size was set to 50; population selection method was based on the roulette wheel, the probability of mutation was 0.06 and the probability of crossover was 0.5. The crossover method is based on uniform and the entire learning process stopped after 10,000 generations.

Minimise

$$\text{fitness} = \left(\frac{\sum_{j=1}^{q} C_j}{q} \right) \tag{5}$$

Where $j=1$ to q, q is the number of training cases. C_j is set to 1 if the expected outcome feature is equal to the real outcome feature for the jth training case. Otherwise, C_j is set to 0.

4.2.2 Varied weights

Chromosomes are designed for encoding a set of feature weights whose the values range was [0..1]. The fitness function is also defined as indicated in Eq. 5. As for the GA parameters, the population size was set to 50, the

Table 1 The case description

Input features	Data type	Range
Alternating current on bright mode when electronic ballast turns on	Continuous	0 to 2 (amp)
Alternating current on dim mode when electronic ballast turns on	Continuous	0 to 2 (amp)
Alternating current on bright mode when electronic ballast turns off	Continuous	0 to 2 (amp)
Alternating current on dim mode when electronic ballast turns off	Continuous	0 to 2 (amp)
Is light unstable when electronic ballast turns on	Categorical	0 and 1
Is it not illuminated when electronic ballast turns on	Categorical	0 and 1
Outcome feature		
Components replacement	Categorical	C_1, C_2, ...,C_{10}

Table 2 Mean errors of different approaches

Approach	Mean error	
	Training	Testing
(a) Linear similarity function with equal weights	0.240	0.223
(b) Linear similarity function with varied weights	0.213	0.220
(c) Non-linear similarity function with equal weights	0.207	0.210
(d) Non-linear similarity function with varied weights	0.200	0.203
(e) Linear similarity function with dynamic weights	0.233	0.230
(f) Non-linear similarity function with dynamic weights	0.193	0.180

probability of mutation was 0.06, and the probability of crossover was 0.5. The entire learning process stopped after 10,000 generations.

4.2.3 Dynamic weights

Chromosomes are designed for encoding values A_i to form a range centered on f_i^I for features that are continuous data. The fitness value is also calculated using Eq. 5 for each chromosome in the population. As for the GA parameters, mutation rate was 0.009, and the other settings were the same as the ones used for varied weights.

4.3 Results

The case base is divided into two data sets for training and testing with the ratio of 2:1. That is, 200 Boeing 747-400 aircraft electric ballast maintenance cases were used for training and the remaining 100 cases were used for testing. The results are illustrated in Table 2. All approaches were evaluated with 3-fold cross validation. The result of approach (F) with non-linear similarity functions and dynamic weighs is the best where the mean error (ME) is equal to 0.193 for training and 0.180 for testing.

To further investigate the results, approach A with linear similarity function and equal weights provided an inferior training result. There is no obvious difference for the testing results of approaches A, B, and E, all of which adopt linear similarity functions. However, among those approaches that do adopt non-linear similarity functions, it seems that approach F, with dynamic weights, has a superior result as compared to approach D with varied weights and approach C with equal weights. It can be inferred that both non-linear similarity functions and the dynamic weighting process are crucial for a CBR system to effectively retrieve previous associated cases.

5 Conclusions

An inefficient aircraft maintenance service may lead to flight delays, cancellations or even accidents. Aircraft maintenance is therefore one of the most important activities airlines do to improve flight safety as well as obtain worldwide competitive strength. To improve the maintenance productivity, this research developed a CBR system with GA mechanisms to enhance the retrieval of similar aircraft electronic ballast maintenance cases. Three GA procedures are proposed to determine the optimal non-similar similarity functions and varied and dynamic feature weights, respectively. The experimental results demonstrated that the approach adopting both non-linear similarity functions and dynamic weights achieves the best performance than approaches with either linear similarity functions or equal/varied weights.

In addition to the electronic ballast, there are numerous components embedded in an aircraft system. The proposed method could also be employed for shorter repair times and lower maintenance costs. Furthermore, aircraft preventative maintenance is also an important issue. In the future, it may be possible to embed such a trouble-shooting component into the aircraft preventive maintenance system based on the history data in flight data recorders (FDR) to help ensure a safer and more comfortable flight.

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